RESEARCH ARTICLE

Navigational Analysis for under water Mobile Robot based on Multiple ANFIS Approach

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ABSTRACT

Multiple neuro-fuzzy inference systems using hybrid learning algorithm as an adaptation mechanism have been focused here for navigation of autonomous underwater vehicle (AUV).The underwatervehiclecanbeexhibitedassix-dimensionalnonlinearandcoupled equations of motion associated with variations of hydro dynamic coefficients which are difficult to model in a realistic manner. Without earlier acquaintance, the feed-forward neuro-fuzzy controller can be directed to obtain the unknown parameters of the model which may aid motion planning strategy of underwaterrobotbyoverlookingthenonlineareffectsoftheAUVdynamics.By amending fuzzy membership function of neural networks, the benefits of fuzzy logic and neural network can be mingled, such as capability of FIS to deal with uncertainty, employing human perception and comprehensive approximation as well as adapting competence of neural networks. ANFIS has been trained with the hybrid-learning mechanism which employs back-propagation-based gradient descent approach and least squares estimate (LSE)to estimate parameters of the model. This approach instigates faster decision- making, obstacle avoidance and also tracking targets. The simulated analysis may authenticate that the heuristic navigational approach is able to negotiate with chaotic environment during navigation of under-water robot.

Keywords: ANFIS, Hybrid learning, Optimal path, Obstacle avoidance, Steering angle, Target seeking behavior.

1. INTRODUCTION

Recently, several control mechanisms for AUV have fetched remarkable research interests. Autonomous Underwater Vehicle sare generally utilized for hazardous underwater tasks, such as, exploration and surveys of potentially dangerous wrecks, rescue operation, surveillance, inspection, recovery, maintenance etc.[1].UVs may be steer able in three directions and can be automated to float reflexively or to dynamically ramble near a preferred location or to move at different depths under water[2].

Due to the difficulty in interaction between the nonlinear dynamic model of AUV and the environment, motion planning for AUV in an ambiguous and cluttered environment leads to demanding control problem[3].Modern control may provide superior execution by adapting the ambiguities of hydrodynamics as well as revealing resistance to in stabilities. Foremost intent is to organize an order of appropriate paths based on updated parameters through online learning method, which enables the vehicle to fulfill its mission by showing obstacle avoidance and target seeking behavior in a combined manner[4]. The flexibility of the fuzzy inference system can be accomplished by either rule base amendment and/or membership functions reformations through learning mechanism of neural networks [5]. Due to the multifaceted profile of AUV, motion control is further challenging to solve as any rotation all motion around any axis may initiate hydrodynamic translational forces and rotating moments [10].

Neuro-fuzzy systems furnish the combination of fuzzy reasoning based on human perception which uses logical

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operators to combine degrees of truth on a numeric scale even under uncertainty, and neural networks which can learn fast without rational model of the system[8]. The simple fuzzy reactive approach in navigation problem intermittently endures two major problems, such as being stuck in local minima and raise in number of rules to cope up with different possible positions of obstacles and targets [11].The proposed approach has the benefit of reduced processing time [7] by introducing weighting factors for activating optimum number of if-then rules based on sensor inputs in crisp values.

The fundamental task of the proposed controller is to make the vehicle to follow a predefined trajectory to reach the final destination [9]. AUVs tender many advantages for performing difficult tasks submerged in water without human intervention in a less expensive way. This paper has beendivided into different sections which can be summarized as follows: Section 2 describes the dynamic model of underwater robot for motion planning analysis. Section 3 presents the formulation of proposed ANFIS algorithm. Section 4 briefly designates online hybrid learning method for ANFIS method. Section 5 exhibits simulated study in MATLAB scenario which contains a number of obstacles scattered in a disorderly fashion. Section 6summaries the contribution of this paper.

2. DYNAMICS OF THE UNDERWATER VEHICLE

The robot has been modelled as a mass which is free to move in the 3D space. The dynamics that have been used are mainly based on the analysis presented by various researchers [3]. The generalizedequations (2.1) and (2.2)of motion for AUV, relative to an inertial frame, can be given by six coupled non-linear differential equations:

$$M(v)\dot{v}+C_D(v)v+g(\eta)+d=\tau \qquad (2.1)$$

$$\dot{\eta}=J(\eta)v \qquad (2.2)$$

Where, $\eta=[x\,y\quad z\ \ \phi\theta\psi]^T$ is the position and orientation vector considering the earth-fixed frame as reference.

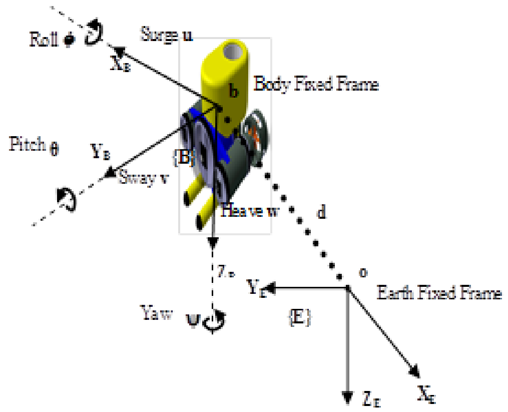

Figure 1.Position and orientation of prototype underwater robot model.

v = [u v w p q r] denotes the velocity and angular rate vector in body-fixed frame as shown in figure 1, M (v) $\in R^{6\times6}$ specifiesthe inertia matrix (including added mass); C(v) $\in R^{6\times6}$ represents the matrix of Coriol is, centripetal and damping term; d signifies the gravitational forces and moments vector along with uncertainty and τ is the input torque vector. J (η)is the transformation matrix and is defined as,

$$J(\eta)=\begin{bmatrix} J(\eta_1) & 0_{6\times6} \\ 0_{6\times6} & J(\eta_2) \end{bmatrix}$$

The position and orientation of the robot can be depicted relative to the spatial frame and the linear and angular velocities are expressed based on the body-fixed frame. The standard notations of SNAME (1950) have been followed here [3]. The vehicle's position and orientation with respect to the earth fixed coordinate system can be represented by a vector,

$$P_B=\begin{bmatrix} x & y & z & \phi & \theta & \psi \end{bmatrix}^T=\begin{bmatrix} b_1 & b_2 \end{bmatrix}^T$$

Velocities of the robot is represented as, $V=\begin{bmatrix} v_c & \omega \end{bmatrix}^T$ and Forces and moments can be denoted as $\lambda=\begin{bmatrix} \lambda_1 & \lambda_2 \end{bmatrix}^T$

where,

$$J(\eta_1)=\begin{bmatrix} c\psi\theta & s\phi s\theta c\psi-c\phi s\psi & c\phi s\theta c\psi+s\phi s\psi \\ s\psi\theta & s\phi s\theta s\psi+c\phi c\psi & c\phi s\theta s\psi-s\phi c\psi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{bmatrix}$$

and

$$J(\eta_2) = \begin{pmatrix} 1 & s\phi t\theta & c\phi t\theta \\ 0 & c\phi & -s\phi \\ 0 & s\phi / c\theta & c\phi / c\theta \end{pmatrix}$$

Heres· = sin(·), c· =cos(·)andt· =tan(·)

The centre of the body-fixed frame is assumed to be located at the centre of gravity with neutral buoyancy due to its symmetric structure. Only three actuators are considered here to guide the robot. Two thrusters for horizontal motion in forward, backward and also for rotation about the z axis and another one for linear motion along z axis. Rotations about the x and y axes cannot exist, so that they are not included in the equations of the system that has been finally used.

3. FUZZY INFERENCE SYSTEM WITH ADAPTIVE NEURAL NETWORK FOR NAVIGATION

To design the architecture of ANFIS, the neural network has to learn about the fuzzy inference system behavior and the gained knowledge will be used to adaptively optimize parameters (antecedent as well as consequent) of the network [1]. Here, three ANFIS models of same structure has been used to find out left horizontal, right horizontal and vertical thruster's speed figureA1.Finally, by using difference method, final steering angle for robot for the current position of robot with respect to target position has been found out from the speed of thrusters computed by ANFIS models.

The first order Takagi Sugeno Fuzzy system has been considered, where each steps(e.g: fuzzification, rule base, inference mechanism and defuzzification) are treated as neural network layers figureA3. For ANFIS model, rules are outlined in a generalized manner as follows in equations (3.1),(3.2),(3.3),(3.4),(3.5),(3.6) and (3.7).

IF x1 is P_i ,x2 is Q_i , x3 is R_i, x4 is S_i THEN f_j= p_j x1 + r_j x2 + s_j x3 + t_j x4+ u_j(3.1)

Where 'i' denotes the number of membership functions. P,Q,R and Sare the fuzzy membership sets specified for the input variablesx1,x2,x3andx4.For jth rule,f_j is the linear consequent function expressed in terms of the inputs along with p_j,r_j,$s_j$and $t_j$as the consequent parameters.

In the ANFIS structure, node sofa layer have same activation functions [6]. The output gained through the node function will be the input data to the next layer as indicated in figure4.

Layer1:The input layer collects data from arrays of sensor inputs x1,x2,x3andx4 which symbolizes the obstacle distances and target angles with respect to current robot position.

Layer2: Each node of this layer denotes a particular fuzzy membership function whose parameters can be altered. Node function stipulates the degrees to which the inputs gratify the quantifier. For four inputs, the outputs from the nodes of layer 2 are given as follows;

$$O_{2,n} = \mu_{M_n}(x) \quad (3.2)$$

Where, x is the input to the nth node of this layer; M= P,Q,R,S are the membership functions for inputs x1, x2, x3 and x4 respectively. Here all membership functions are considered as bell shaped function figure A2 which is depicted as follows;

$$\mu_{M_n}(x) = \frac{1}{1+\left\{\left(\frac{x-c_n}{a_n}\right)^2\right\}^{bn}} \quad (3.3)$$

Where a_n, b_n and c_n are the variables for the fuzzy membership function [2].c_n signifies the centre of the corresponding membership function; a_n is the half width; and $b_n/2a_n$ restraints the slope at the cross over points:

Asbell-shaped function figureA2 can modify its pattern with the change in values of parameters the membership functions of linguistic label M_n may have different forms of representation as per requirement of data set of the problem.

Layer 3: This layer does not contain any activation function. The output of each node is the product of all incoming values to that specific node which is a circular one (fixed) symbolized as "π".

$$O_{3,m} = w_m = \mu_{P_n}(x) * \mu_{Q_n}(x) * \mu_{R_n}(x) * \mu_{S_n}(x) \quad (3.4)$$

The outcome of each node of this layer embodies the firing strength(degree of fulfilment) of the associated rule.

Layer 4: As normalized firing strength can be achieved as an outcome of layer 4, each node is labelled as "N" (fixed node). Number of nodes of layer 4 is same as layer 3. The output can be expressedas,

$$O_{4,m} = \bar{w}_m = \frac{w_m}{\sum_{m=1}^{n} w_m} \qquad (3.5)$$

where, 'n' is the total number of membership functions used in layer 2 for fuzzification of all input signals.

Layer 5: Number of nodes for this layer is same as that of the previous one. Here, each node has a linear adaptive function. The output can be expressed as,

$$O_{5,m} = \bar{w}_m f_m = \bar{w}_m (p_m x1 + r_m x2 + s_m x3 + t_m x4 + u_m) \qquad (3.6)$$

where, $\{p_m, r_m, s_m, t_m, u_m\}$ is the premise parameter set and $\bar{w}_m$is the normalized firing strength from layer 4.

Layer6:The single node of this layer, identified as "Σ", can give the defuzzified crisp value for actual thruster's speed which has been computed here as the summations of all output signals from layer five or previous layer.

$$O_{6,i,e} = \sum_{m=1}^{n} \bar{w}_m f_m = \frac{\sum_{m=1}^{n} w_m f_m}{\sum_{m=1}^{n} w_m} \qquad (3.7)$$

This whole procedure has been repeated to determine Horizontal and Vertical Thruster's speed along with different sets of parameters for antecedent and conclusion parts of ANFIS. In order to attain a preferred input-output mapping, these parameters have to be revised according to the assigned training input/output data. After computing Thruster's Speed, Actual Steering Angle can be calculated by using difference method.

4. HYBRID LEARNING ALGORITHM FOR ANFIS MODEL

Hybrid learning scheme combines Back propagation based gradient descent method and least square estimate (LSE) for ascertaining variables or parameters of a network [8]. As ANFIS network has only one output that can be represented as a function of input variables and parameters it can be denoted as F(I,G) shown in equation (4.1).

Where, I: Vector representation of input variables; G:A set of parameters for both antecedent andconsequent portions of the network. The parameter set G can be distributed into two sets G_1(antecedent:a_n,$b_n$andc_n) andG_2(premise:$\{p_m,r_m,s_m,t_m,u_m\}$)

Assume a function J such that the combined function JoF is linear in elements of G_2, subset of G. The elements of G can be found by u single act squares method through the following computation,

$$J(output) = J \circ F(\vec{I}, G) \qquad (4.1)$$

For given values of G1, training data D can be added to the equationand the equations can be gathered in matrix from:

$$BZ = C \qquad (4.2)$$

Z is a matrix form of the parameter set of G2 with dimension Mx1. The dimension of B is DxM and dimension of C (training data) is Dx1.As the number of linear parameters (M) is lesser than the number of training data (D), the exact solution cannot be evolved. So, least square estimate of Z, Z * can be acquired. The most recognised formula for Z* in equation (4.3) is:

$$Z^* = (B^T B)^{-1} B^T C \qquad (4.3)$$

Where,B^T is the transpose of B and if $B^T B$is non-singular then $(B^T B)^{-1} B^T$ is the pseudo inverse of B. When $B^T B$ issingular, sequential method of Least Square Estimate is the only method to get the solution in equation (4.5):

$$Z_{i+1} = Z_i + G_{i+1} b_{i+1} (c_{i+1}^T - b_{i+1}^T Z_i) \qquad (4.4)$$

$$G_{i+1} = G_i - \frac{G_i b_{i+1} b_{i+1}^T Z_i}{1 + b_{i+1}^T Z_i}, i = 0,1,\ldots,D-1 \qquad (4.5)$$

Where, b_i^T : i-th row vector of matrix B; c_i^T : the i-th element of matrix C. G_i is the covariance matrix and least square estimate Z* is Z D. InitiallyX_0=0 and G0 =σ I ; where I is the identity matrix with dimension MxM and σ is a positive large number.

Within the forward pass [8], fuzzified version of input data associated with given values of G1 has been taken for calculation of each node output until B and C given in equations (4.2) is found and then the parameters in G2 will be acquired by the sequential least squares formula in equations (4.4). Then outputs from middle layers will be guided towards the final single output.

In case of backward pass, the error is circulated from output end to input end and parameter set of G1 can be revised through gradient descent method. Suppose the given training data seth as D entries, the error measure (or energy function) for the pth (1≤d≤D) entry of training data entry can be stated

As the sum of squared errors in equation(4.6)[3,8]: $E_d = \sum (T_d - O_d)^2$ (4.6)

Where, T_d is the desired output and O_d is the tangible output. Then the overall error measure is in equation (4.7):

$$E = \sum_{d=1}^{D} E_d \qquad (4.7)$$

Forth edth training data, according to gradient descent method, the error rate for the output node at layer L may be estimated as,

$$\frac{\partial E_d}{\partial O} = -2(T_d - O_d^L) \qquad (4.8)$$

For the internal node at(l,m) layer l index m, error rate can be obtained by the chain rule:

$$\frac{\partial E_d}{\partial O_{m,d}^{l}} = \sum_{k=1}^{\#(l+1)} \frac{\partial E_d}{\partial O_{k,d}^{l+1}} \frac{\partial O_{k,d}^{l+1}}{\partial O_d^{l}} \qquad (4.9)$$

Where, $1 \le l \le L-1$

This rate of error for an internal node may be depicted as a linear combination of the rate of errorsfor nodes of the next layer. Hence, for all $1 \le l \le L$ and $1 \le m \le n$, $\frac{\partial E_d}{\partial O_{m,d}^{l}}$ can be found by using equations (4.8) and (4.9). Suppose for given the adaptive network, β is a parameter, the details of equations are shown in equations (4.10),(4.11),(4.12) and (4.13).

then $\frac{\partial E_d}{\partial \beta} = \sum_{O^* \in Y} \frac{\partial E_d}{\partial O^*} \frac{\partial O^*}{\partial \beta}$ (4.10)

Where,Yisthe setofnodes whose outputdependsonβ.

Then the derivative of the overall measure E with respect to β is

$$\frac{\partial E}{\partial B} = \sum_{d=1}^{D} \frac{\partial E_d}{\partial \beta} \qquad (4.11)$$

Therefore, the renew formula for the parameterβis $\Delta\beta = -\lambda \frac{\partial E}{\partial \beta}$ (4.12)

Where λ is the learning or adaptation rate which can be conveyed as:

$$\lambda = \frac{s}{\sqrt{\sum_{\beta} (\frac{\partial E}{\partial \beta})^2}} \qquad (4.13)$$

Where s is the step size which denotes the span of each gradient shift in the parameter space. The value of s can be improved to vary speed of convergence.

5. SIMULATION STUDIESOF3D NAVIGATION

During path planning, the instantaneous information can be acquired by the underwater robot sensors. Steering angle towards the position to be reached from the current position of the underwater robot can be computed using ANFIS toolbox whose dataset (for training and testing purpose) has already been collected from experimental investigations. In present investigation, maximum no. of iterations for ANFIS training has been set as 200 (epochs) and the error has got to be asymptotic. The training RMS error was found to be 0.0156 as shown in figure A4.The scatter plot of FIS output versus training dataset and testing dataset are displayed in figure A5and figure A6separately. It was also found that the predicted values of steering angle are nearer to the actual values. Simulated studies on path planning in 3D environment have been shown for endorsing proposed method. When the values from any sensors are slightly less than the threshold values (35mm), obstacle avoidance behaviour has to be initiated. Collision avoidance has the highest priority as shown in figure A7. When the mobile robot senses both target and obstacle in same direction, the wall following behaviour would be executed to avoid local minima.

The robot must turn clockwise or anticlockwise such that it can make parallel movement along the wall as shown in figure A8. Preliminary robotic behaviours have been conquered here through a number of training patterns of ANFIS.

6. CONCLUSION

The learning mechanism of implemented algorithm allows AUV to adopt knowledge on behaviour by cooperating with the environment. The inadequacy in knowledge due to uncertainty and nonlinearity can be disregarded by employing the rule-base of ANFIS which can reflect fusion of all robotic behaviours. AUV motion can be controlled in both vertical plane and horizontal plane. Using ANFIS tool box, the obtained mean of squared error (MSE) for training data set in the current paper is 0.0156.The obtained results from the above model was analysed in a number of simulated experiments using MATLAB and it validates the feasibility of the proposed method. The hybrid learning based ANFIS may have shown optimal effect to some extent by using updated information about the target and obstacles concurrently, but the gained path may not be globally optimal. Simulation results show the success of algorithm as robot moves smoothly towards its target avoiding collision. Further studies with experimental verification of simulated results will be performed using proposed method.

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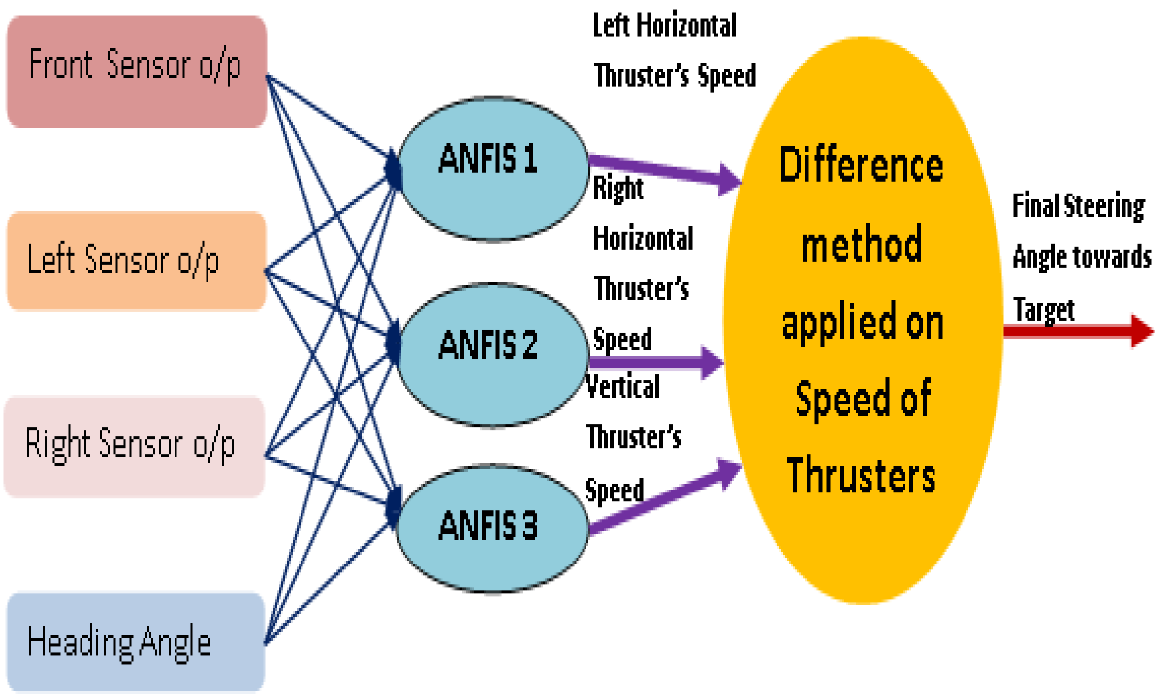
APPENDIX A



FigureA1.BlockdiagramofmultipleANFISmodelsforunderwatermobilerobotnavigation.

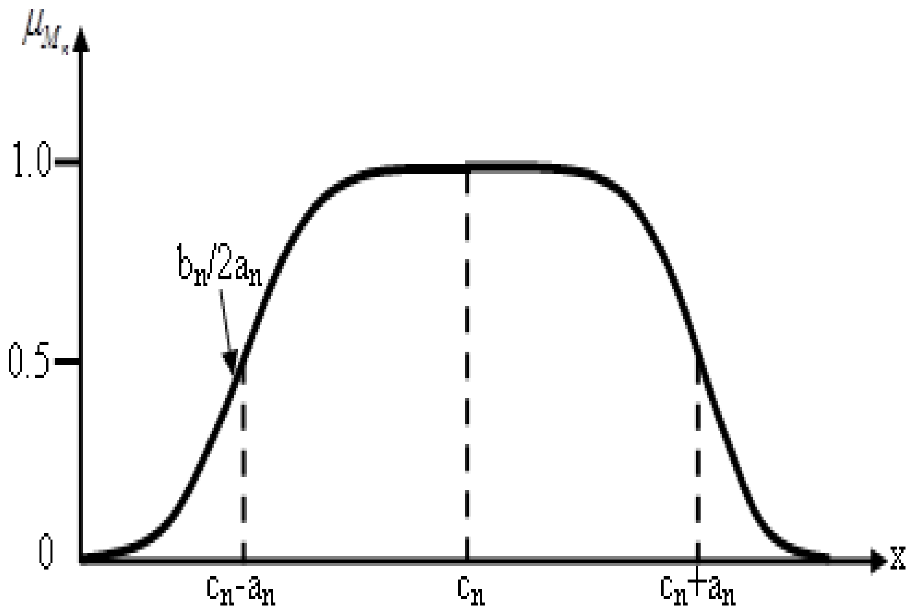


Figure A2. Bell shaped membership function used for fuzzy inference system

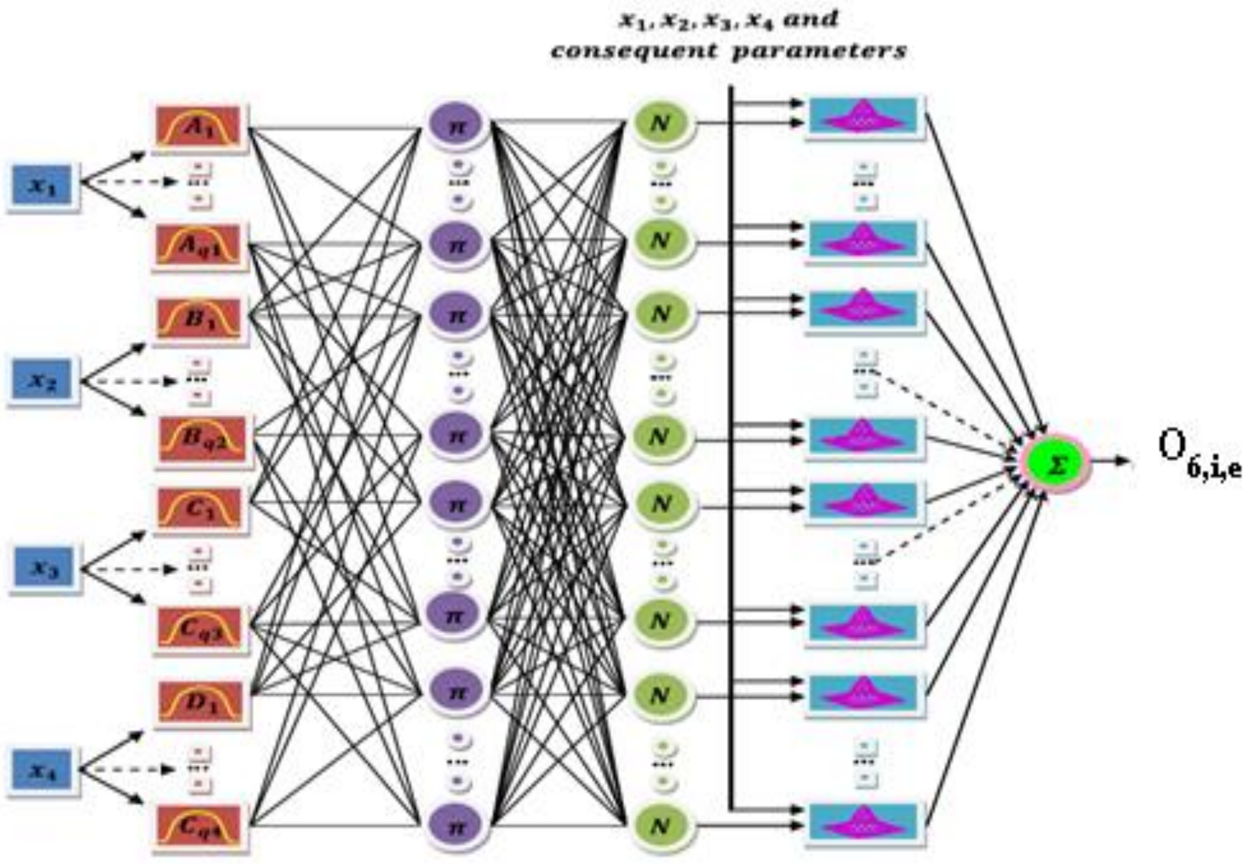


Figure A3. ANFIS architecture of six layers

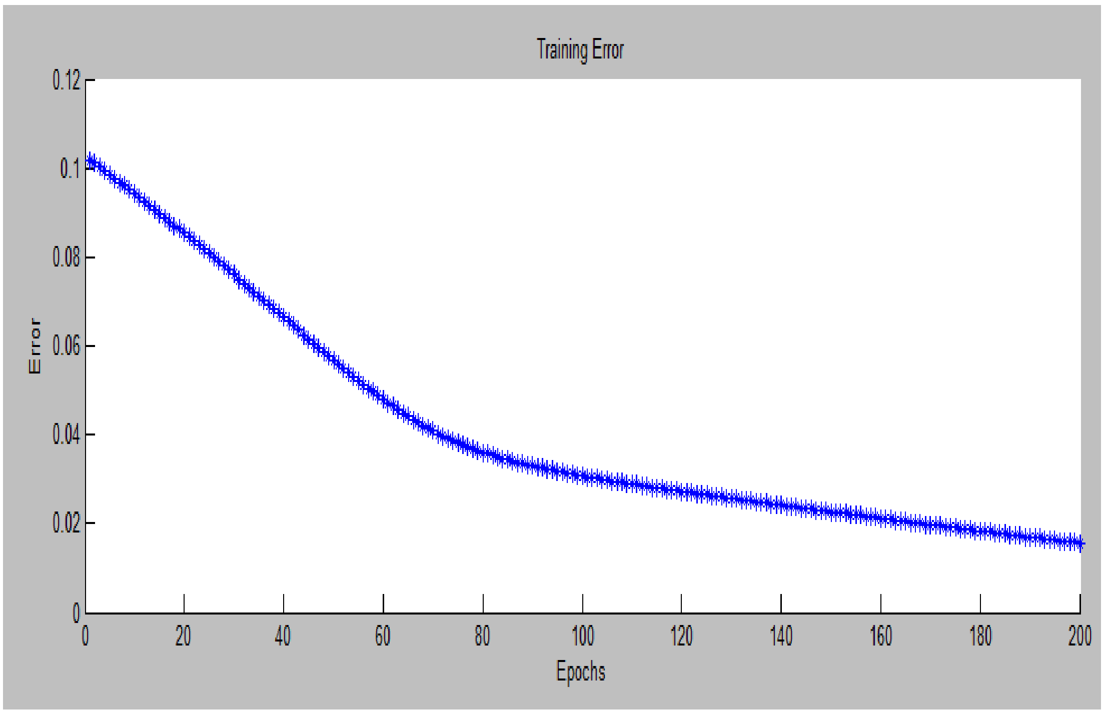


Figure A4. Mean square error versus epoch number corresponding to training data

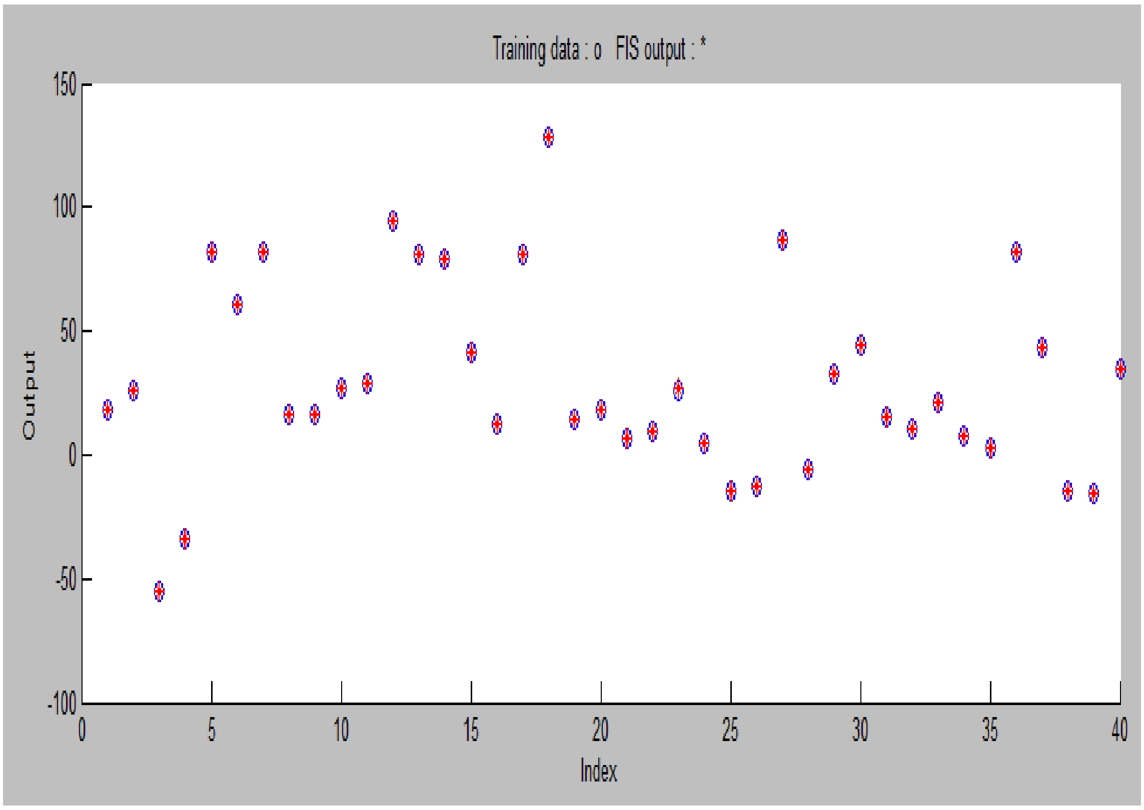


Figure A5. Scatter of FIS output and training data

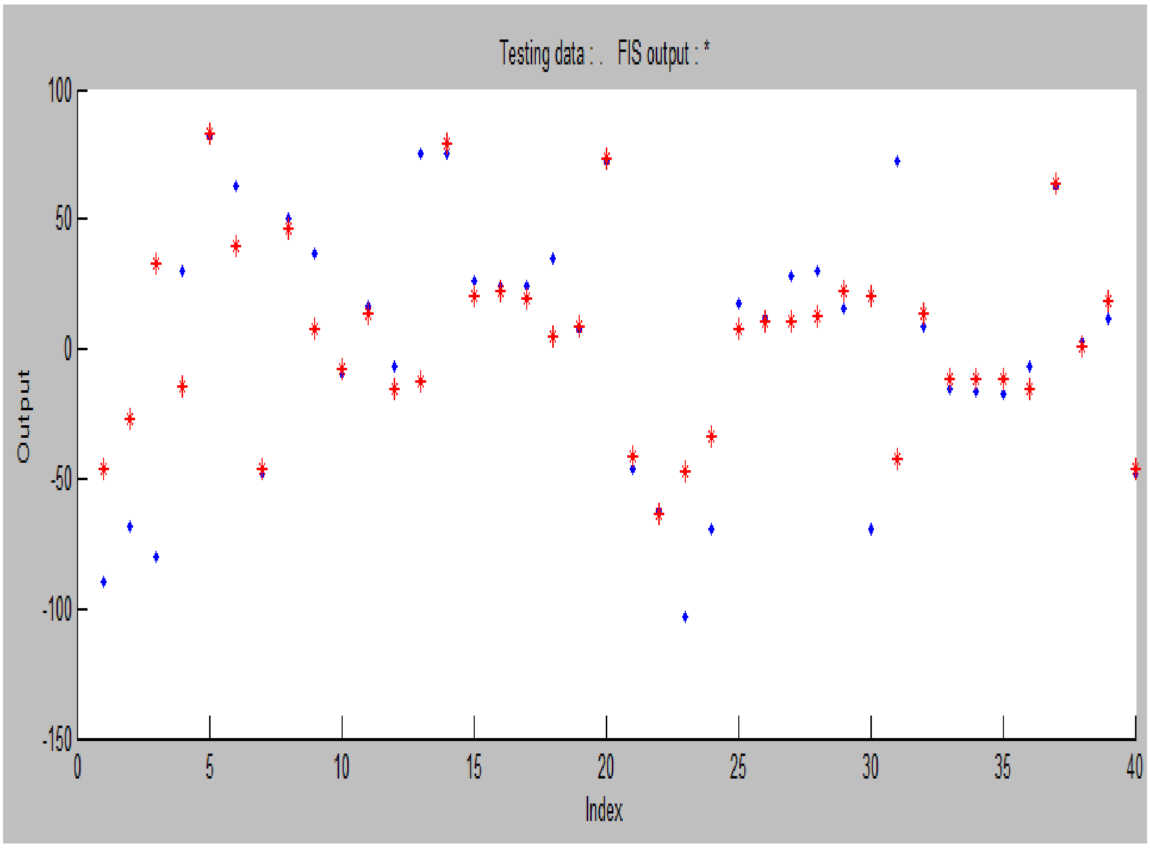


Figure A6.Scatter of FIS output and testing data

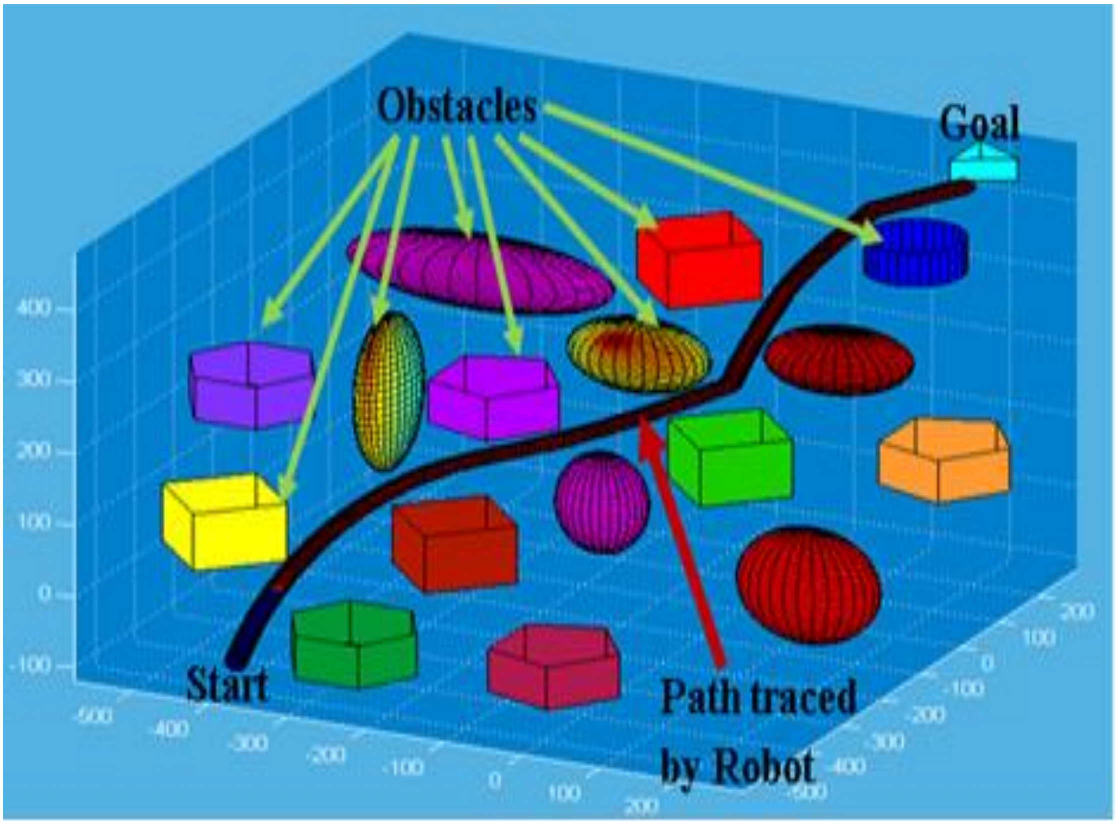


Figure A7.Static obstacle avoidance behaviour

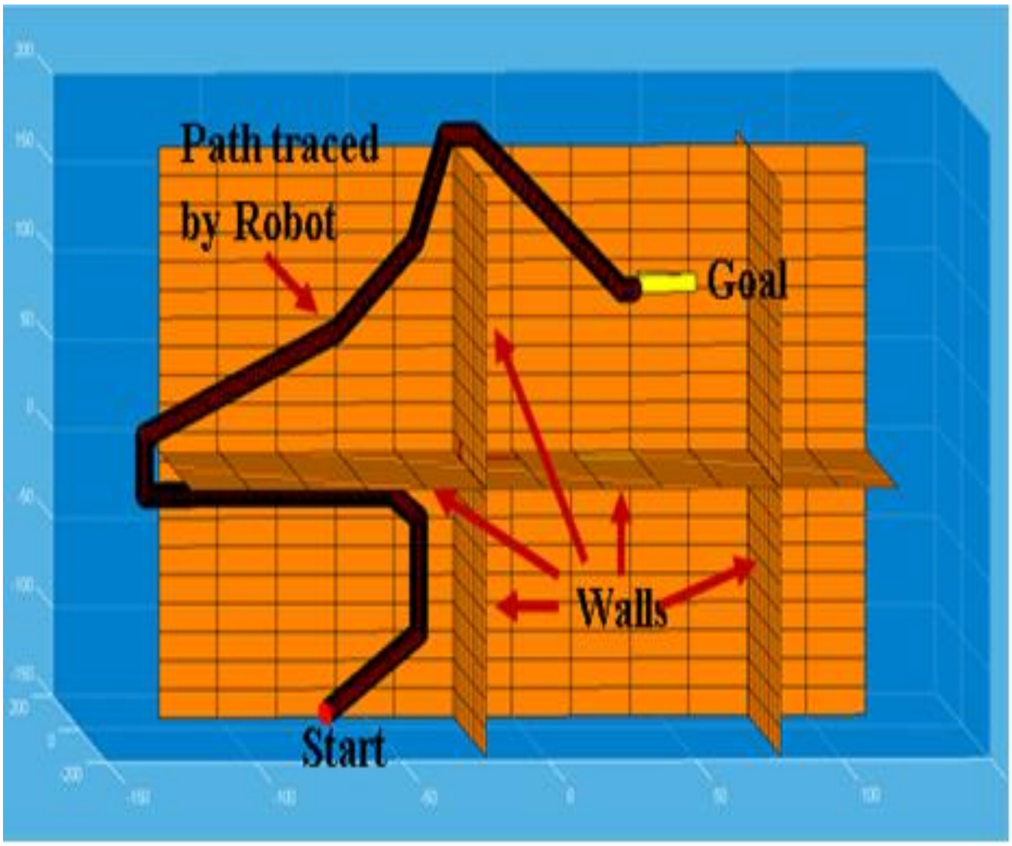


Figure A8.Navigational path traced based on obstacle avoidance and target seeking behaviour